Environmental Preferences of Yellowfin Tuna in the North East Indian Ocean: An Application of Satellite Data to Longline Catches

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Abstract: Development of state-of-the-art methodologies to minimise search time and to increase the fishing efficiency of high seas fishery are vital for fishing success. It, minimise the operational cost as well as fishing duration that save the fish quality. Understanding of the ocean environment and their preferences of Yellowfin Tuna (YFT) are important aspect to addresses the fishing uncertainty thereby ensuring the expected catch during a short period of time. Environmental parameters such as temperature, chlorophyll and dynamic height of the sea surface were obtained from remote sensing satellites and a YFT catch dataset was obtained from Sri Lankan longliners. The results of the data analyses have shown that the relationships between oceanographic parameters and YFT catch rates were found significant. These relations are capable of predicting fishable aggregations of YFT using near-real time satellite observations. High frequencies of YFT catches were found in the areas where Sea Surface Temperature (SST) varied primarily between 28-30°C. The corresponding Sea Surface Heights (SSH) ranged from 205-215 cm and Sea Surface Clorophyll_a (SSC) concentration ranged from 0.1-0.4 mg/m^3. The relationships between catch rates and the three environmental variables have been tested with the Empirical Cumulative Distribution Function (ECDF). The degrees of differences between the ECDF and catch-weighted cumulative distributions of the three variables are statistically significant ($p<0.01$). The strongest association showed between catch rates and SSC while SSH showed the lowest. The results obtained from a Generalized Additive Model (GAM) have shown that the space-time factor is well above the ocean environmental factors and the oceanographic factors are also in significant levels ($p<0.05$). Therefore, the migratory pathway is an essential factor in predicting YFT inhabitants in the northeast Indian Ocean.

Keywords: ECDF, fishing ground forecast, GAM, GLM, Indian Ocean, satellite data, *Thunnus albacores*

INTRODUCTION

Tunas, the family Scombridae are reported to be found in tropical oceans around the world ocean and account for a major proportion of the world's fishery products (Collette and Nauen, 1983). Sri Lanka is one of the important tuna producing Island and its fisheries statistics have shown that the YFT, is the most important tuna species among the six species recorded (Joseph *et al*., 1985). With the increasing demand for YFT tuna in the export market, more and more efforts have been exerted using longlines and Gillnets. However, longline has become more popular than gillnets as it preserves the freshness of the fish, but uncertainty of catch brought wider spectrum of problems to the industry. Uncertainty of catch leads to increase search time, operational cost and low quality fish landings. As a result the catch being failed to export, even with high operational cost and the revenue become less. The purpose of this study is to examine the relationship between YFT occurence in relation to

the oceanographic conditions in the northeast part of the Indian Ocean (Fig. 1).

Indian Ocean is greatly influenced by two wind systems known as southwest and northeast monsoon causing characteristic seasonality of temperature, phytoplankton, ocean currents and mixed layer properties. YFT distributed over large oceanic extent of fishing potential due to this seasonality of oceanographic condones. The distribution of YFT cause longer search time which costly and time consuming. Therefore, predicting fishable aggregations make the search more efficient and economic. To achieve this, it would be useful to analyse long-term fisheries and oceanographic data that could affect the temporal and spatial distribution of YFT (Zagaglia *et al*., 2004).

Previous studies have shown that the distribution of tuna species is greatly influenced by oceanographic conditions such as sea surface temperature (Sund *et al*., 1981; Ramos *et al*., 1996), hydrographic fronts (Laurs *et al*., 1984; Laurs and Lynn, 1977; Fiedler and
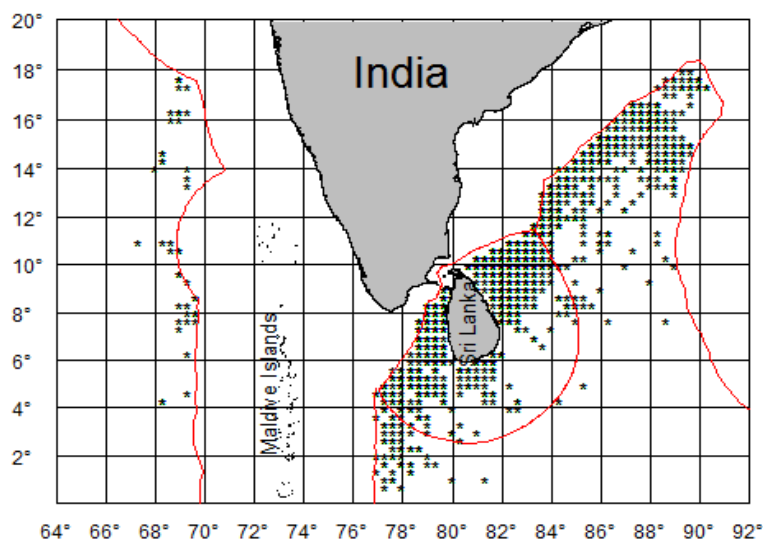
Fig. 1: Study area showing the positions of fishery dataset obtained during 3-year period from 2006-2008. The positions are shown 1/3°grids

Bernard, 1987; Stretta, 1991; Kimura *et al*., 1997) and depth of thermocline (Ueyanagi, 1969). Hence, it is reasonable to assume that these factors may have influence on the abundance and distribution of YFT. Limited studies have been carried out in the Indian Ocean to understand the fisheries oceanography of YFT.

Remote sensing techniques show great potential to support successful exploitation of pelagic fishery resources and global fisheries management (Santos, 2000; Yamanaka *et al*., 1988). This technology has proven to be a useful tool to study oceanographic features such as thermal fronts, eddies where tunas are reported to be aggregated. The combination of satellite and biological data could be used to identify habitat preference and migrating routes of YFT leading to predict potential fishing grounds. Several attempts have been made to study the associated movements and catch rates with environmental conditions (Uda, 1973; Stretta, 1991; Power and May, 1991; Ramos *et al*., 1996; Browdwr *et al*., 1993; De Rosa and Maury, 1998; Bigelow *et al*., 1999).

This study reveals the likelihood of YFT vulnerability to longlines with respect to the temperature, chlorophyll and dynamic heights of the sea surface in space and time.

MATERIALS AND METHODS

Two types of data sets consisting fishery and satellite derived oceanographic parameters were obtained for the period of three years (2006-2008). To meet the objectives of this study, oceanographic data derived from satellites, were obtained to match with fisheries data.

SST data were obtained as blended products from two sensors with improved spatial resolution (1/4°) and temporal resolution (3-day). The two sensors are Advanced Microwave Scanning Radiometer (AMSR) and Advanced Very High Resolution Radiometer (AVHRR) on the NASA Earth Observing System satellites. The SST products also included a large-scale adjustment of satellite biases with respect to *in-situ* data obtained from ships and buoys (Reynolds *et al*., 2007).

Corresponding SSC data were obtained from Moderate resolution imaging spectroradiometer (MODIS) onboard Terra and Aqua satellites in 4 km spatial resolution. The data are distributed by NASA gsfc (http://oceancolor.gsfc.nasa.gov/ftp.html). Ocean colour products such as chlorophyll_*a* (SSC) were contaminated by clouds. To remove cloudy pixels and to increase the coverage, successive images were composited by assuming that the SSC is not considerably varies within the averaging period in the region. The minimum period of composting to remove the cloudy pixels was found to be 15 days with images taken from the two platforms (Terra/Aqua). Therefore, initially 15-day SSC composite image was constructed and successive 3-day interval time series was generated by updating the initial image.

SSH data were obtained from the information collected by TOPEX/Poseidon and ERS satellite altimeters (ftp://ftp.cls.fr/pub/oceano/AVISO/). The data were available at archiving, validation and interpolation of satellite oceanographic data (AVISO) in net CDF format. These data (1/3°) were obtained in 3-day composites that contain the parameters such the date, latitude, longitude and sea surface dynamic height with respect to the geoid.

Fishery data were collected from Sri Lankan longliners and the dataset is consisting of fishing date, position, number of hooks and catch. Fishing effort is depend on varies factors such as number of fishermen

in each trip, number of hooks and availability of fish for the bait and bait types etc. There are many factors that determine the likelihood of a particular hook catching a fish, including the depth of hook, bait type, availability of live food, timing and location of effort. Fish behaviour also a factor (Ferno and Olsen, 1994); not all fish that are present will come close enough to detect the bait, not all fish that detect the bait will bite it and not all fish that do bite bait will get caught on the hook. Longline configuration and hooking depth used in a particular area can result very poor catch rates depending on the vertical distribution. Considering all these catch uncertainties, null catches have been removed from the dataset. It is also important to point out that this CPUE cannot consider as a good index of relative fish abundance. Therefore the CPUE can be considered as indices of fish availability to Sri Lankan longlines, but not as indices of fish abundance. Water temperature, search time, catch of bait or bate type, hooking depth, catch weight and weather conditions were almost absent in logbooks. Owing to the lack of this information the effort data were not standardized. Therefore, Catch Per Unit of Effort (CPUE) was defined as number of fish per 100 hooks per day regardless of the catch weights.

The resolution of SST data was 1/4° and SSH data was 1/3° while SSC has 4 km. All the image data were gridded into the lowest resolution (1/3°). The SST and the corresponding SSH data were taken in 3-day composites while updating SSC initial image in every 3-day interval to coincide with the SST and SSH. The length of longlines vary between 10-15 miles and the drift due to ocean currents during the deployed period (4-6 h) is 5-10 miles. Thus, the long-line data fall within the minimum resolution of the satellite data (1/3°). Therefore, the CPUE data were also gridded into 1/3° and averaged over 3-day fishing activity assuming that the SST, SSC and SSH are not significantly varies within the 3-day periods. Fishery and satellite derived oceanographic parameters were matched up and the outputs were further analysed.

The association between the three oceanographic variables and CPUE were analysed using Empirical Cumulative Frequency Distribution Function (ECDF). In this analysis, three functions (Perry and Smith, 1994; Andrade and Garcia, 1999) were used as follows:

$$f(t) = \frac{1}{n}\sum_{i=1}^{n} l(x_i) \qquad (1)$$

With the indication function:

$$l(x_i) = \begin{cases} 1 \ if \ x_i \leq 1 \\ 0 \ otherwise \end{cases}$$

$$g(t) = \frac{1}{n}\sum_{i=1}^{n} \frac{y_i}{\bar{y}} l(x_i) \qquad (2)$$

$$D(t) = max|f(t) - g(t)| \qquad (3)$$

where $f(t)$ is empirical cumulative frequency distribution function, $g(t)$ is catch-weighted cumulative distribution function, $l(x_i)$ is indication function and $D(t)$ is the absolute value of the difference between the two curves $f(t)$ and $g(t)$ at any point t and assessed by the standard Kolmogorov-Smirnov test. n is the number of fishing activities, x_i the measurement for satellite-derived oceanographic variables in a fishing activity i, t an index ranking the ordered observations from the lowest to highest value of the oceanographic variables, y_i is the CPUE obtained in a fishing activity i and $\bar{y}$ the estimated mean of CPUE for all fishing activities. The maximum value of $D(t)$ represents specific values of the oceanographic variables at which the highest CPUE can be obtained.

Optimizing favourable oceanographic conditions: Two statistical models, Generalized Additive Model (GAM) and Generalized Linear Model (GLM) were applied to identify the nature of relationships between YFT and the three ocean environmental parameters. The relationships between environmental factors and CPUE are mostly expected as non-linear. Once the shape of the relationships between the response variable and each predictor was identified, the appropriate functions were used to parameterize these shapes in the GLM model. Generalized linear models have been used to study CPUE variability of YFT in the eastern Pacific Ocean (Punsly, 1987; Zagaglia *et al.*, 2004).

The shapes resulting from the GAM were reproduced as closely as possible using the piecewise GLM. Three environmental variables were included in the analysis using a GAM Eq. (4) and a GLM Eq. (5), as follows:

$$\ln(CPUE) = a + s(SST) + s(CHL) + s(SSH) + e \qquad (4)$$

$$\ln(CPUE) = b + b_1(SST) + b_2 ln(CHL) + b_3(SSH) + e \qquad (5)$$

where, a and b are constants, $s(.)$ is a spline smoothing function of the variables (SST, SSC and SSH) and e is a random error term, $b1$, $b2$ and $b3$ are the vectors of model coefficients.

GAM is a non-parametric generalization of multiple linear regressions which is less restrictive in assumptions of the underlying statistical data distribution (Hastie and Tibshirani, 1990). The GAM has no analytical form but explain the variance of CPUE more effectively and flexibly than the GLM. The GLM was constructed based on the trend of YFT CPUE in relation to the predictors estimated by GAM with the least different residual deviance (Mathsoft, 1999). GLM estimates a function of mean response (CPUE) as a linear function of some set of predictors. Hence, the GLM fit was used to predict a spatial distribution of potential habitat for YFT.

The GLM were fitted using a Normal distribution as the family associated with identity link function

(McCullagh and Nelder, 1989). The data distribution and the link function in the GLM were exactly the same as those used in the GAM. A logarithmic transformation of the CPUE was used to normalize asymmetrical frequency distribution. The model selection process for the best predictive model for explaining CPUE data was based on a forward and backward stepwise manner. The predictors were considered to be significant in explaining the variance of CPUE, if the residual deviance and Akaike Information Criteria (AIC) decrease with each addition of the variables and the probability of final set of variables was lower than 0.01 (p<0.01).

RESULTS

Frequency distribution of YFT fishable SST is primarily varies between 26-31°C and more catches have been taken in the areas where SST varied between 28-30°C (Fig. 2a). The tendency of temperature is centred at 29°C where more frequencies of catches have been taken. Sea surface chlorophyll concentrations of YFT catches shows below 1.0 mg/m^3 although it can be observed higher (>1.0 mg/m^3) concentrations in the area. The SSC distribution of YFT falls between 0.0-0.8 and negatively skewed within this range (Fig. 2b). Frequency of YFT fishing days in relation to sea surface height follows a Gaussian distribution. The distribution of SSH indicates that YFT were found in areas where sea surface height ranged from 185-235 cm (Fig. 2c). However, the most catches have been obtained from the waters where SSH varies from 205-215 cm (210±5 cm) while it slightly varies over the year.

Monthly variability of CPUE Fig. 3a doesn't show a considerable variation or any seasonality of YFT catches. Thus, the YFT fishable aggregations are available in the area throughout the year although the spatial distribution of YFT is varying depending on the prevailing oceanographic conditions. SST of fishable aggregations is around 27°C in January and it increases to about 30°C in April and then gradually decreases till August (28.5°C). Then SST increases again to ~30°C in October and down to about 27.5°C in December. YFT aggregations are found in warmer (28.5-3°C) waters during inter-monsoons and relatively cooler waters (27-28.5°C) during NE and SW monsoons (Fig. 3b). Monthly variation of SST of fishable YFT shows an identical pattern followed by each year. Thus, SST can be used to locate YFT aggregating areas using this feature. Monthly variation of sea surface chlorophyll_a (Fig. 3c) does not show such an identical pattern, but the best range for YFT availability between 0.2-0.4 mg/m^3. Sea surface height (Fig. 3d) of YFT also show a seasonal variability that also useful for locating YFT aggregations.
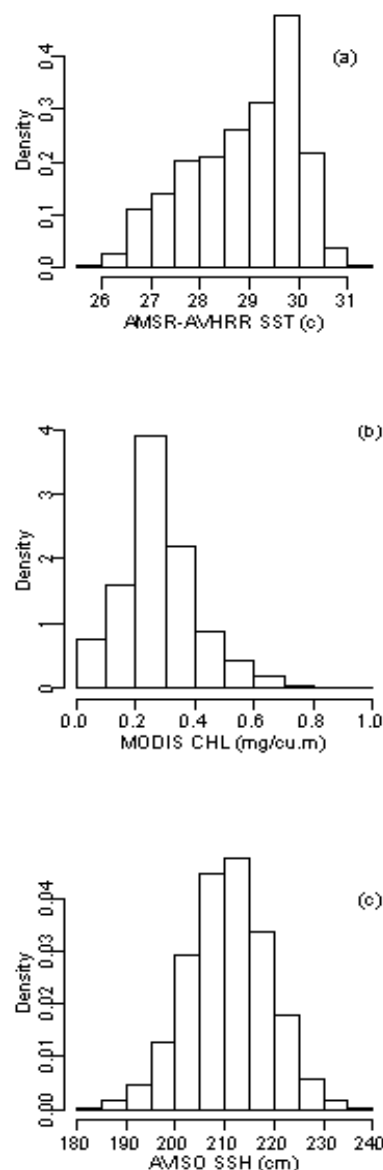

Fig. 2: Histograms showing frequencies of YFT caught SST (a), SSC (b) and SSH (c) in the NE Indian Ocean

The relationship between CPUE and the three environmental variables above have been proven by the empirical cumulative distribution function (ECDF). The cumulative distribution curves of the three variables are different and the degrees of the differences between the two curves are highly significant (p<0.01) for SSC.

The results showed a stronger association between CPUE and the variables, with SSC ranging from 0.1-0.4 mg/m^3 (Fig. 4c), slightly lower association with SST ranging from 28°C to 30°C (Fig. 4a). The lowest association exist with SSH ranging from 205-215 cm (Fig. 4b). The highest association of the three variables occurred at 29.3°C SST, 0.3 mg/m^3 SSC and 205 cm SSH and the catch rates tend to be decrease at the outside of those ranges.
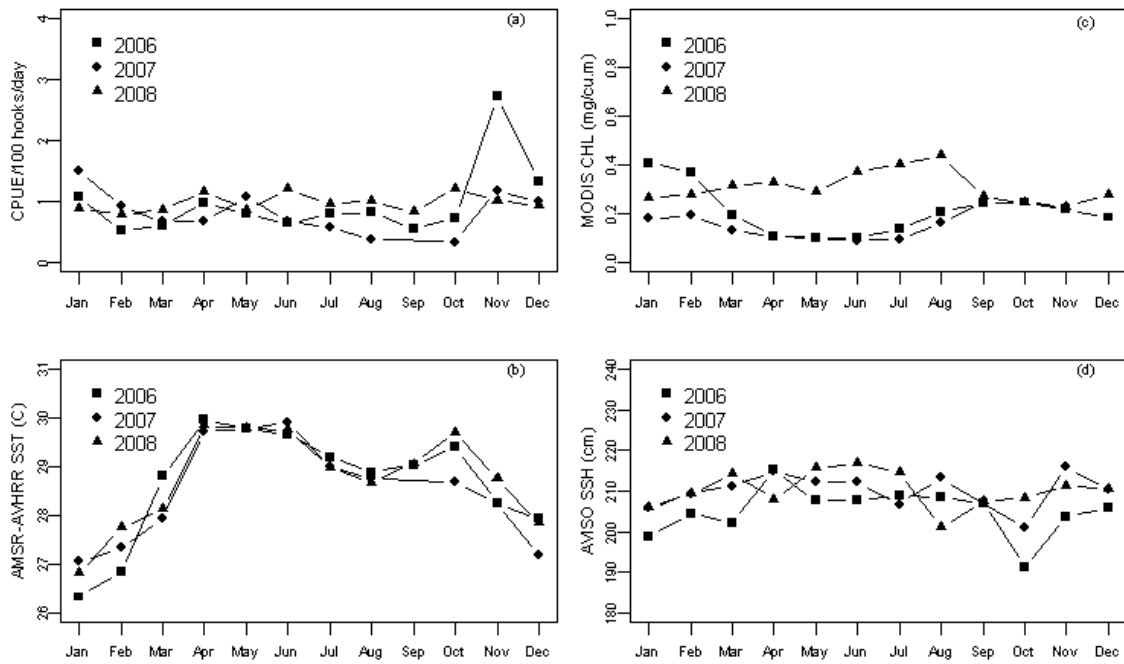
Fig. 3: Monthly variability of CPUE (a) and corresponding variability of SST (b), SSC (c) and SSH (d) during the period
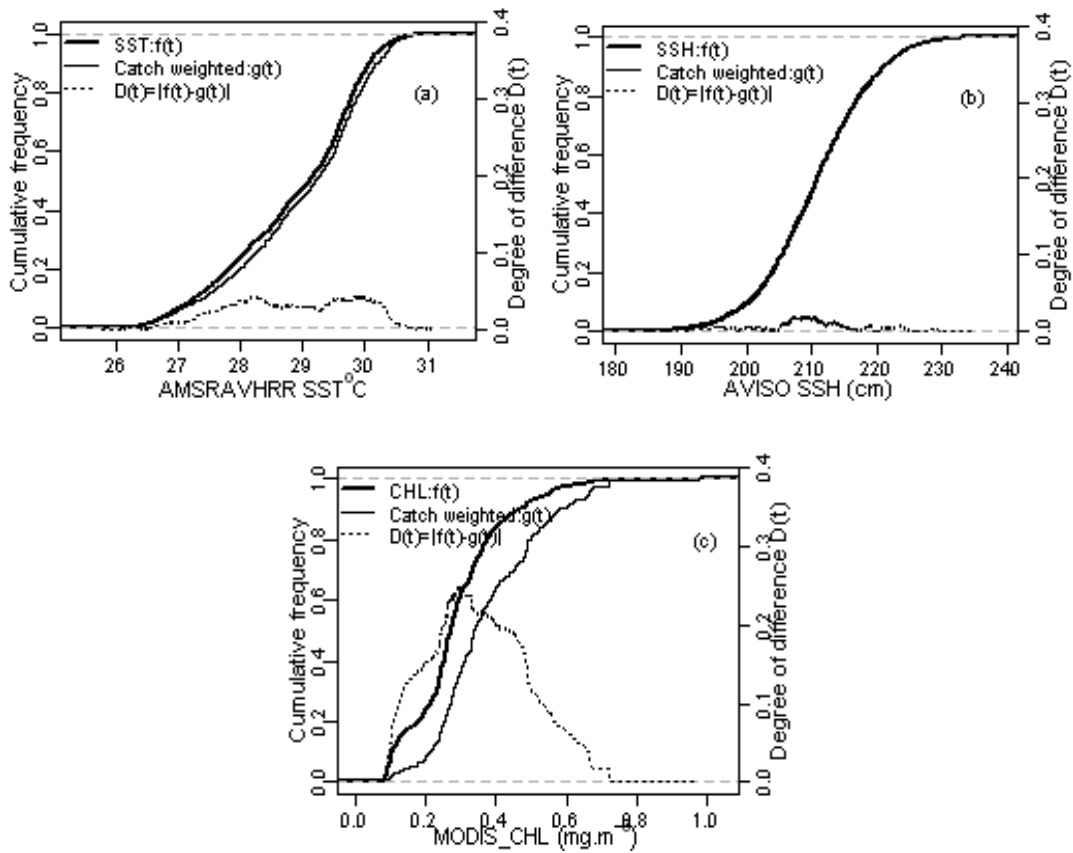

Fig. 4: Empirical cumulative distribution frequencies of SST (a), SSH (b) and SSC (c) superimposed of YFT catch weighted SST, SSC and SSH. The dashed-lines show the degree of differences of the two curves
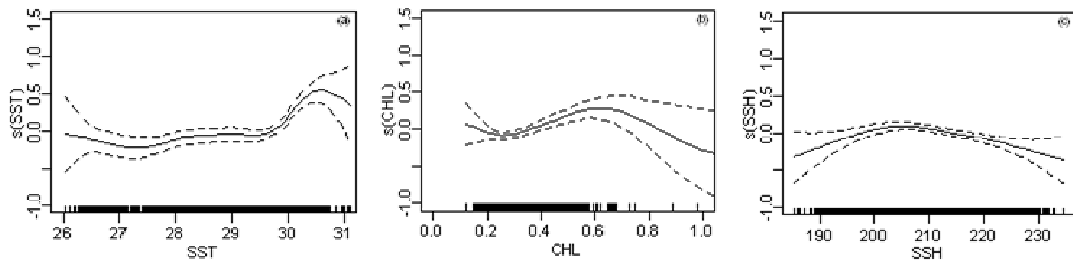
Fig. 5: Generalized Additive Model (GAM) derived effect of oceanographic variables SST (a), SSC (b) and SSH (c) on YFT CPUE (log transformed). Dashed line indicates 95% of confidence intervals
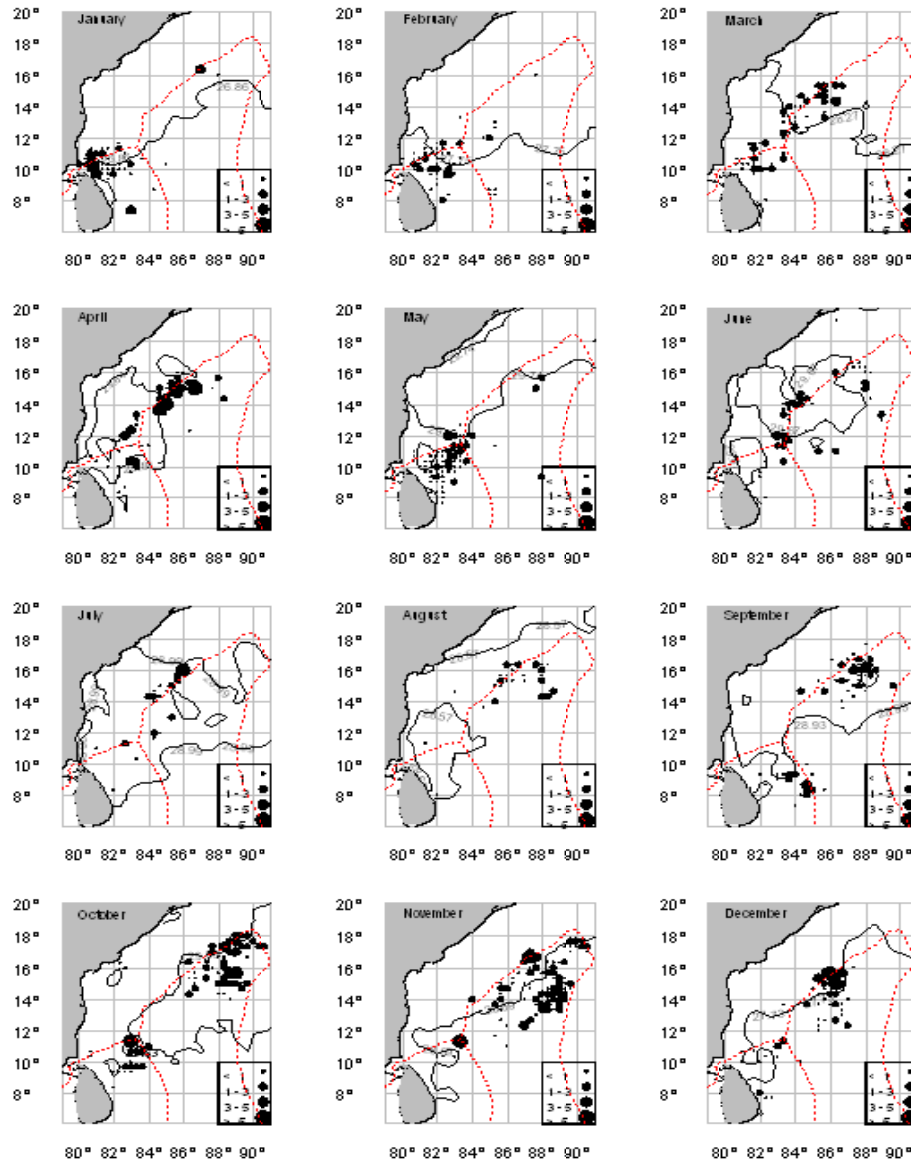

Fig. 6: Monthly average SST contours that have high potential fishable aggregations of YFT (Fig. 3b) with superimposed of actual CPUE (dots). This shows the space time factor is more effective in predicting fishing grounds on favourable SST ranges

The GAM results show that the SST influences on YFT catch rates and the SST (Fig. 5) is not only the parameter that predicts YFT potential habitats in the northeast Indian Ocean. Indeed, the SST has been used

Table 1: Single predictor GAM fits for YFT in fishing ground. For each predictor, the percentage of deviance and the generalized cross validation score is given

Parameter	% devience	GCV score
SST	4.63%	0.67658
CHL	2.57%	0.69039
SSH	1.5%	0.69595
lat×lon×month	19.9%	0.5965

Table 2: Significance of the smooth terms included in the GAM for YFT occurrence in fishing grounds

	S.E.	t-value	p	n
Intercept	0.01526	0.774	0.437	1673
Variable	edf	F	p	
SST	6.620	8.216	<0.001	
CHL	5.786	5.913	<0.001	
SSH	2.905	7.791	<0.001	

Table 3: Deviance and GCV scores of YFT CPUE of fishing grounds explained in GAM with variables added

Variable	Residual d.f.	Residual deviance	GCV score	Cumilative variance
Mean	1664.8	1120.8		
SST	1659.7	1098.8	0.67658	4.63%
CHL	1656.7	1077.3	0.66729	6.5%
SSH	1611.8	903.76	0.65667	8.33%

Table 4: Construction of GLM as each variable is added, residual deviance, the approximate AIC and F-statistic for YFT availability in the fishing grounds

Variable	Residual d.f.	Residual deviance	AIC	F
NULL	1672	1175.2		
SST	1671	1147.3	4122.7	40.665
CHL	1670	1132.9	4103.6	21.182
SSH	1669	1125.2	4094.2	11.423

to describe tuna habitats as it relatively easy to obtain and the SST become particularly very useful in finding strong surface thermal gradients, where the fishing grounds are normally located (Laurs and Lynn, 1977; Laurs *et al.*, 1984).

The space-time factor (lat/lon and month), explains the largest portion of the data variance (Table 1), being the most significant factor amongst all the independent variables included in the model. This explains the migratory behaviour of YFT described earlier, where the largest CPUE observed close to Sri Lanka during the early year and moving parallel to the Indian coast towards Bangladesh waters (Fig. 6).

The relationship between the given predictor and the density of YFT was analyzed according to the percentage of deviance explained and the GCV scores of the GAM models (Table 1). Space (lat/lon) and time (month) were the best predictor explained the density of YFT with the highest deviance (19.9%) and the lowest GCV score (0.5965) and it was subsequently followed by SST (4.63%), SSC (2.57%) and SSH (1.5%). The environmental factors, SST, SSC and SSH, being statistically significant as shown by associated *p*-values (Table 2).

The environmental parameters, SST, SSC and SSH, showed associated *p*-values well below those found for the space-time factor (Table 1). In fact,

considering their p-values (p<0.05) the oceanographic parameters are also in significance levels. Therefore, the environmental parameters influence on the CPUE of YFT in the Northeast Indian Ocean (Table 3 and 4).

DISCUSSION

Offshore/high longline seas fishery has been begun in 80's and its inefficient development has been caused by several limitations. Fleets developments and fishing technology were the main areas that have not been developed in this fishery. However, fishermen used their gathered knowledge and experience during the short histry of longline fishing. Single-Side-Band radio communication have been helping them to reach potential fishing areas. Sri Lankan longlines operates in very shallow depths (50-75 m) due to onboard manpower for hand-hauling the fishing lines. The shallow depth of tuna existance can be considerd as feeding grounds. This existance is explained by Nishida (1992) using two stock structure that is western and eastern stocks mixing around Sri Lanka in their migratory path. The fishermen have been able to follow the migratory paths wih their experiences and communication. Longlines are operating comparatively deeper (100-130 m) waters in the south of Sri Lanka.

Null catches might not be due to the less abundance, but it may be due to other factors such as line oprating depth, bait used, area and time factor, availability of live food, prevailing oceanographic and weather conditions. However, it has been assumed that the dataset represent the real availablity of YFT in relation to environmental parameters such as sea surface temperature. The reported CPUE of YFT in the present study was comparatively lower than the other fishing fleets in the Indian Ocean. This may be due to several factors such as fleet capacity, operating depth, suitable baits, onboard technology and the overall knowledge on fishing skills.

Limited fishery data were used in this study although longer time series data provide more precise representation of YFT with respect to the environment. Combinations of SST data with SSC and SSH have provided fishable conditions of YFT in time and space. Hence, the oceanographic parameters themselves do not adequate to predict the potential fishing grounds and required to combine the space/time factor. The space time factor provides the information of YFT migratory pattern.

The results showed that catchable aggregation of YFT can be located using SST which specific to a time period. The highest CPUE exist within a narrow SST range (~1°C) between 28.0-30.0°C depending on the time of a year. This implies that the SST does not represent the preferred living temperatures of YFT, although a chronological SST can be used to locate more abundant areas combining the migratory pathways. It has been proven that the YFT live slightly above thermocline helping them to reach favourable

temperature ranges. Thermocline is the layer where rapid decrease of temperature gradient occurs. It fluctuates from about 50-100 m in the northeast Indian Ocean due to seasonal monsoons wind stress. As a result the depth of YFT abundance in the water column may affect by tending vertical migration. Deepening of the thermocline may affect the vulnerability of YFT to shallow longlines by Sri Lankan fishermen. Brill *et al.* (1999) found that the depth of the mixed layer is more important than the SST for YFT abundance. According to their findings, adult YFT are found to be immediately below the mixed layer and juveniles are associated in much shallow areas. However, the present study does not reveal the correlation between the mix layer depth and the CPUE since less information available in the dataset. Knowledge of the relations between CPUE and thermocline depth can be used to locate fishing grounds accurately.

According to Stretta (1991), YFT prefers warmer waters and the abundance of this species was higher with temperature limits between 18-31.0°C. In the tropical Atlantic, most of YFT catches have been obtained with temperatures between 22.0-29.0°C and preferentially above 25.0°C. The flat relationship of the temperature is evident that the distribution of YFT in the Brazil coast within the range of 26-28.5°C (Zagaglia *et al.*, 2004). By these observations it has been concluded that the SST values above 28.0°C seem to form a pathway of favourable thermal conditions to the migratory movements of YFT (Zagaglia *et al.*, 2004). The result of this study is also consistent with the other findings in tropical waters. Therefore, SST is an important predictor for YFT that represented not only by the temperature but also correspondence with space (lat/lon) and time factor (Fig. 6).

The optimum SSH ranges for the abundance and distribution of YFT in the northeast Indian Ocean was estimated 200-220 cm with some temporal variations. The importance of SSH to predict YFT fishing grounds have been discussed by various authors (Zagaglia *et al.*, 2004). The relationship between SSH and CPUE may vary considerably as SSHA (Sea Surface Height Anomaly) is a complex combination of dynamical and thermodynamical factors, which could affect in opposite ways the concentration of the fishing resources (Zagaglia *et al.*, 2004).

Based on the results, the YFT fishable oceanographic parameters in the northeast Indian Ocean were characterized by SST of 28-30°C, SSC of 0.1-0.4 mg/m^3 and SSH 200-220 cm. These results are very similar to the previous studies in relation to SST (Uda, 1973) and CHL (Polovina *et al.*, 2001). The results of this study were confirmed by statistical models.

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